

Multifractal analysis of sEMG signal of the complex muscle activity

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September 11, 2014

Abstract

The neuro-muscular activity while working on laparoscopic trainer is the example of the complex (and complicated) movement. This class of problems are still waiting for the proper theory which will be able to describe the actual properties of the muscle performance. Here we consider the signals obtained from three states of muscle activity: at maximum contraction, during complex movements (at actual work) and in the completely relaxed state. In addition the difference between a professional and an amateur is presented. The Multifractal Detrended Fluctuation Analysis was used in description of the properties the kinesiological surface electromyographic signals (sEMG). Based on the results obtained in the form of multifractal spectra together with the parameters which effectively describes it, like the spectrum half-width, or the Hurst or the singularity exponents, we demonstrate the dissimilarity between each state of work for the selected group of muscles as well as between trained and untrained individuals. For the well-trained person (professional) at work mf-spectrum shows similarity with the relaxed state, i.e. the spectrum will be truncated at the right side which show the dominance of the low fluctuations. On the contrary the spectrum for the untrained person at actual work will tend to be rather broad and symmetric. This feature hidden in the sEMG fluctuations allows for the determination of the level of training not only in the case of surgeons but also opens a possibility for similar analysis in any other complex motion with the use of the noninvasive surface electromyography.

Keywords: multifractal analysis, Hurst exponent, electromyography

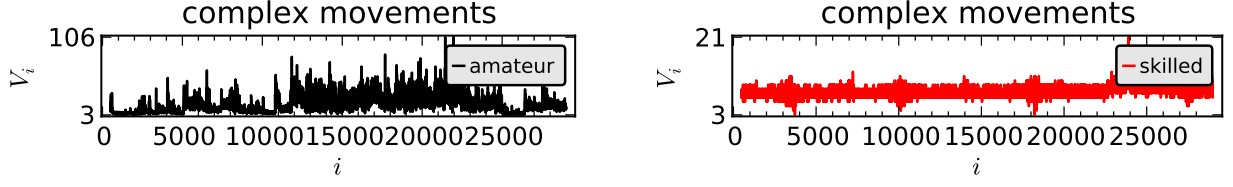
1 Introduction

In the last few decades the detrended fluctuation analysis (DFA) method has become a one of the standard techniques for the computation of the fractal scaling properties [1]. It also serves as a great tool for the detection of long-range correlations nonstationary time series. Another very celebrated method is based on the wavelet transformation of the signals [2, 3] which together constitutes widely accepted methods of the fluctuation analysis. In 1941 Kolmogorov introduced multifractal formalism [4] in the context of analysis of the turbulent data. It was extensively developed in the last decade of the last century [5, 6] and still attracts considerable attention which includes such a distant fields like the biological systems [7], financial markets [8, 9], econophysics [10], turbulence [11], space data analysis [12], physiology [13] or medicine [14, 15] to mention but a few.

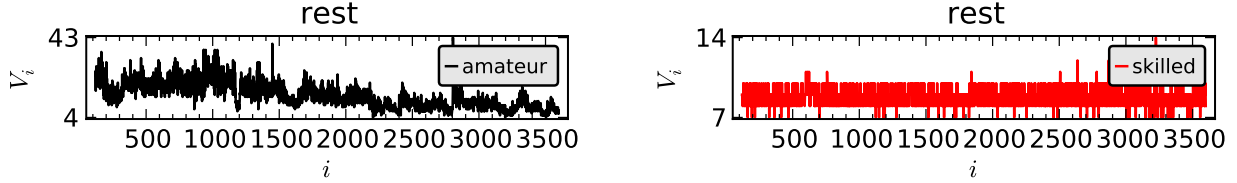
The electromyography (EMG) together with the electrocardiography, electroretinography and electroencephalography are nowadays not only the diagnostic instruments in medicine but constitute the proper and powerful scientific tool based on the electro-physiological activities of our body [16]. In particular the surface EMG (sEMG) has become a promising apparatus for the non-invasive analysis of muscles [17, 18]. The standard analysis of the sEMG signal covers usually three aspects: the activation level of the muscle membrane potential, impact of the forces exerted on the muscle and the degree of muscle fatigue. In this work on the contrary we will employ the multifractal analysis of the electromyogram in order to extend the typical analysis of the sEMG time series. The classical (mono-) fractal aspects [19, 20, 21, 22] has also been extensively analysed for example in the context of force of contraction of different muscles [23].

Electromyography itself implies several challenges. It concerns an inappropriate location of the electrodes over the group of muscles [24], variation of the distance between the electrodes during the measurement and finally modification of the source position in relation to each electrodes. These in turn will influence the morphology of the series and can manifest as a change of the shape, but most of all can affect the signal's amplitude. Another

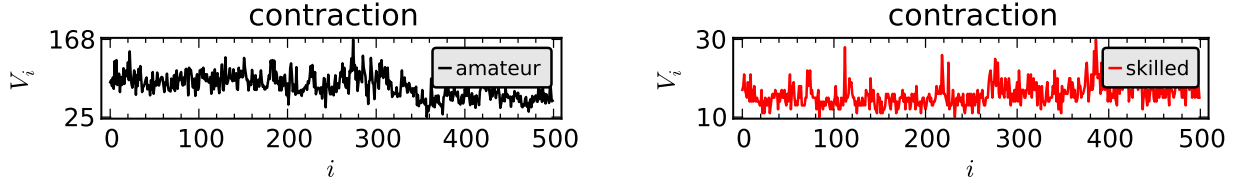
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(a) Signals obtained from muscle at complex work. The task was to tie the standard surgery knots using the laparoscopic tools.



(b) Signals obtained from muscle in the relaxed state.



(c) Signals obtained from muscle at maximum contraction.

Figure 1: Data collected from the channel 1 (in the vicinity of the trapezius ridge) for amateur (left column, black) and professional (right column, red) at three different states.

important aspect is the cross talk, which is defined as the influence from the activity of the neighbouring muscles. The last mentioned problem which can have quite a large contribution to the systematic error is the inter-individual variability. This has a particular meaning in the situation when we want to compare two or more individuals. This in general is caused by the different tissue characteristics, which include the thickness of adipose tissue, skin electrical resistance, sweating, hydration and the thickness of epidermis.

The paper is organized as follows. In the next section we will describe the experimental setup. Next we will report the details of the multifractal analysis. We will end with the conclusions and summary.

2 Set-up

We have performed the measurements on two individuals - a highly skilled one and a complete beginner. They were given the complex task which should be performed on the laparoscopic trainer. The task was to tie the standard surgery knots using the laparoscopic tools. Usual recording time took around 60 minutes and the signal was collected from four groups of muscles, trapezius ridge (channels 1 and 5), deltoids (ch. 2 and 6), long palmar muscle and ulnar wrist flexor (ch. 3 and 7) and abductor muscle of thumb and flexor brevis (ch. 4 and 8). Channels 1–4 and 5–8 were linked to the left and the right upper extremity, respectively. The measurements were conducted with the portable 8 channel surface EMG recorder (OT Bioelettronica, Torino, IT) with the bipolar surface circular AgCl electrodes of size 15x15 mm. The inter-electrode distance was set to 10 mm.

The system automatically records the maximum value of the signal from each of the active channels. The Amplitude Rectified Value (ARV) measured in μV was collected on MVC (maximum voluntary contraction) recording mode. The ARV is mean value of the rectified EMG over a time interval T (125ms). The range of bandwidth was from 34 to 340 Hz. The signal amplitudes were in the range of a few μV to even more than 1000 μV , see figure

1(a) for details. Additionally, we recorded the signals from the relaxed muscles – the recorded person was asked to sit down and reduce the mobility for a few minutes. This record consists of around 3500 data points (about seven minutes), see figure 1(b). The third measurement corresponds to the muscle in the strong contraction – both subjects were supposed to keep 1 kg with arms bent and kept in parallel to the ground. As it is quite hard to maintain such a posture for a long time, this data are the shortest and consists of only few hundreds measurement points (a little over a minute), see figure 1(c).

There are visible differences in the electric potential generated by the muscle cells for all three different states presented in figure 1: the complex task (a, top row), the rest state (b, middle row) and the strong constant contraction (c, bottom row). There is also a significant difference in the level of the muscle activity between a skilled person and an amateur. The amateur has about five times greater amplitude of the signal. The most probable cause for this lies in the different characteristics of the tissue, like the thickness of the skin and the adipose tissue which in turn leads to the different skin impedance for both cases.

3 Multifractal analysis

In the following we will present the typical Multifractal Detrended Fluctuation Analysis (MFDFA) as presented in [25] and [26]. In short, the analysis requires the following stages. Suppose that we have time series with N data points $\{x_i\}$, we perform than four consecutive steps

- (i) Calculate the profile y_i as the cumulative sum from the data with the subtracted mean

$$y_i = \sum_{k=1}^i [x_k - \langle x \rangle]. \quad (1)$$

- (ii) The cumulative signal is split in N_s equal non-overlapping segments of size s . Here, for the width of the segments we use the power of two, $s = 2^r$, where $r = 4, \dots, \lfloor \log_2(N/10) \rfloor$. Larger segment sizes will result with rather weak statistics. Typically the length of the data will not be accordant with the power of two and some data would have to be dropped from the analysis. Therefore the same procedure should be performed starting from the last index, and in turn the $2N_s$ segments will be taken into account.
- (iii) Calculate the local trend $y_{v,i}^m$ for v^{th} segment by means of the least-square fit of order m . Then determine the variance

$$F^2(s, v) \equiv \frac{1}{s} \sum_{i=1}^s (y_{v,i}^m - y_{v,i})^2 \quad (2)$$

for each segment $v = 1, \dots, N_s$. The same procedure has to be repeated in the reversed order (starting from the last index). Next determine the fluctuation function being the q^{th} statistical moment of the calculated variance.

$$F_q(s) = \left(\frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(s, v)] \right)^{\frac{1}{q}}, \quad q \neq 0, \quad (3)$$

$$F_0(s) = \exp \left\{ \frac{1}{4N_s} \sum_{\nu=1}^{2N_s} \ln [F^2(s, \nu)] \right\}, \quad q = 0. \quad (4)$$

The above function needs to be calculated for all segment sizes $s = 2^r$. We have exploited several different orders of the fitted polynomials and end up with no statistical difference between the results. Here we will present the analysis with the quadratic fit.

- (iv) In the last step the determination of the scaling law of the fluctuation function (3) is performed by means of the log-log plots of $F_q(s)$ versus segment sizes s for all values of q . The function $F_q(s) \sim s^{h(q)}$ is naturally smaller for the smaller fluctuations, which results in the increasing function with the increasing segment size. From the calculated Hurst exponent $h(q)$ we are able to determine several quantifiers. Firstly, we work out the mass exponent using the formula

$$\tau(q) = qh(q) - 1. \quad (5)$$

Secondly we can obtain the singularity exponent $\alpha(q)$ by applying the Legendre transform. The last quantifier and the main result of the MFDFA method is the singularity spectrum, given by

$$D[\alpha(q)] = q\alpha(q) - \tau(q). \quad (6)$$

The detailed information on how to read the singularity spectrum can be found in the literature [14, 27, 28]. Multifractality is an indication of the complex dynamics where the single exponent (like the fractal dimension) will not be enough to describe the phenomenon. In the case when the data exhibits not just one individual exponent the continuous spectrum of exponents should be taken into account.

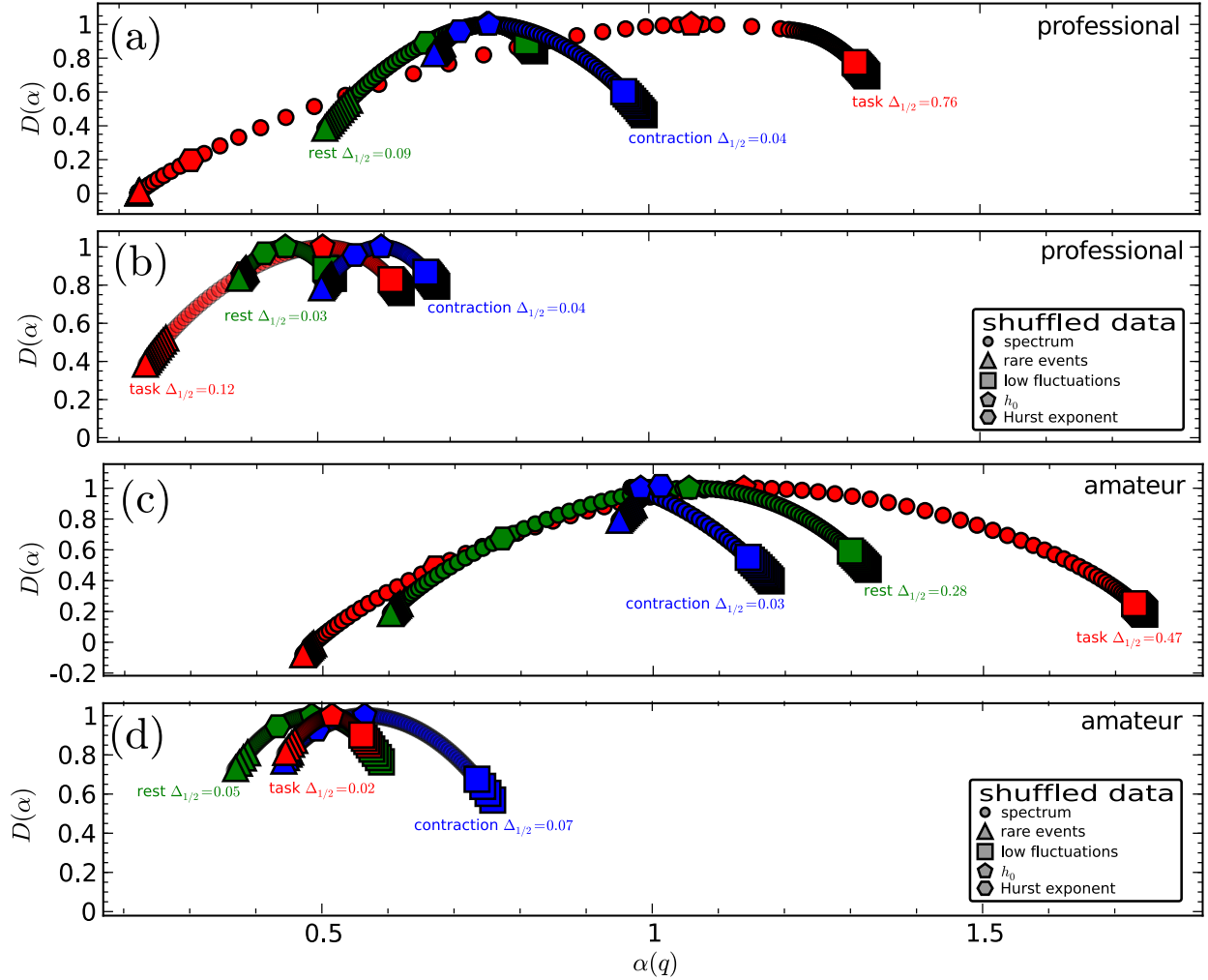


Figure 2: (color online) The multifractal spectrum for channel 1 (in the vicinity of the trapezius ridge) for professional (a,b) and amateur (c,d). On each panel three curves depict the multifractal spectrum corresponding to the three states of the performance of the muscle group: executing complex task (red), at rest (green) and at the maximum contraction (blue). The panels (a) and (c) present the spectra for the original data, while the panels (b) and (d) show the spectra for the shuffled data. All figures have the same width for the sake of comparison.

4 Multifractal spectra at complex work

The central result of this work is presented in figure 2. The plot presents the multifractal spectrum. This relation is defined as the singularity spectrum as the function of the singularity exponent $D = D(\alpha(q))$. The multifractal spectrum describes how often the irregularity of certain degree occurs in the signal. $D(\alpha)$ represent q -order singularity dimension and $\alpha(q)$ stands for the q -order singularity exponent (6). It illustrates the variability in the fractal structure of the time series. The monofractal time series has dense mf-spectrum around the single point $(H, 1)$, where H is the global Hurst exponent [29]. To investigate the scaling properties of our data the analysis of the the position of the maximum value of the mf-spectrum, the global Hurst exponent itself, the half-width and the extremes of the mf-spectrum have to be taken into consideration [14]. The whole analysis was performed for all 8 channels. We have calculated the q -th order fluctuation function $F_q(s)$ for 100 values of the invert power $q \in [-5, 5]$

with the step equal to 0.1 as suggested in the literature [26].

There are two general sources of multifractality which can affect the shape of the mf-spectrum: (i) one is due to the broad probability density function which lies behind the data (or its fluctuations); (ii) second is driven by the different behaviour of the (auto)correlation function for large and small fluctuations; (iii) both situations simultaneously. Simple data shuffling can test the possible source of multifractality. In the case (i) shuffling will not change the mf-spectrum, for (ii) will destroy the effect completely as the shuffling will destroyed the possible correlations; in the last case (iii) the spectrum will differ from the original one-shuffled series will exhibit somehow weaker multifractality. For the all analysed cases the correlation for large and small fluctuations seem to be the main factor which causes the strong multifractality [30] – please compare pairwise panels (a) – (b) and (c) – (d) in the figure 2. For the presented analysis this is the usual effect for all of the spectra except for the working state for the professional and the maximal contraction state for the amateur. The Hurst H exponent for all of the cases behaves however in a similar way for the shuffled data. In the working state after shuffling the estimated values are very close to 0.5 which suggest that in this very case we deal with the white uncorrelated white noise. This means that the correlations are the only source of multifractality (case ii). The other states show a little bit higher (contraction) and lower (rest) values of H than in the work state, which may suggest some sort of the monofractal behaviour (again after shuffling) – see panels (b) and (d).

The shape and the width of the multifractal spectrum provide the information about the local changes of the Hurst exponent. We can see that the value of the spectral width is different for different states of muscular tension for both individuals. A large difference between periods when small and large fluctuations takes place increases in turn the width of the spectrum. The analysis of the signal where neither weak nor strong local fluctuations dominate will result in the symmetric shape of the mf-spectrum. This aspect is visible for the sequence of the nonprofessional performing full task – see the red curve in figure 2(c) for details. On the contrary the study of the corresponding signal but for the professional exhibits the dominance of the low local fluctuations. This feature is also clearly visible in the raw signal, see figure 1(a) on the r.h.s. This situation is a manifestation of the influence of the training for the resulting electrical potential generated by group of the examined muscle cells. The trained person will use his locomotor system very effectively, allowing only simple and necessary movements. Therefore the resultant spectrum will in general express close similarity to the spectrum for activity system at rest – compare green curve in figure 2(a). Both just described states will show the dominance of the low fluctuations, which is an indicator of the weak excitations in muscle cell membranes. On the contrary the spectrum for the untrained person at actual work will show rather broad and symmetric multifractal spectrum. The rare events are as distant from the maximum value as low fluctuations and as result neither weak nor strong fluctuations dominate in the signal. Even at the rest state the spectrum is rather wide and symmetric, which indicate constant excitations from the electrical activity of the muscle cell membrane – i.e. even at rest the amateur will unnecessarily exploit the energy.

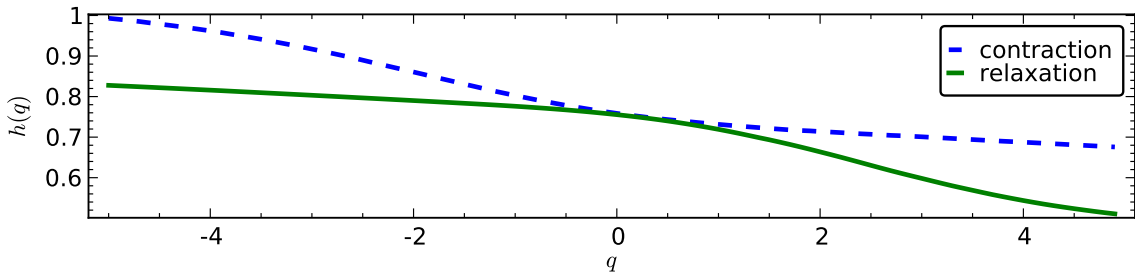


Figure 3: q -order Hurst exponent $h(q)$ for the series with the dominance of the small (green, solid) and large (blue, dashed) local fluctuation for professional.

The time series, or rather its fluctuations, exhibit similarity for both individuals only in the state of the full contraction. The natural tendency to strong excitation of the cell membranes will result in the predominance of the high fluctuations. This is visible as the high variability in the signal (figure 1(c)), as a mf-spectrum with the left truncation or as the leveling of the q -order Hurst exponents positive q 's, see blue dashed curve in figure 3 for details.

The difference of the multifractal structure in the local fluctuation with small and large variation is visible also on $h(q)$ and $\alpha(q)$ dependence, which respectively presents Hurst and singularity exponent as a function of q . For the $h(q)$ dependence see figure 3 for details. The $\alpha(q)$ is calculated as the tangent slope of the mass exponent

$\tau(q)$ (5). For monofractal signals (or similarly for the white noise) the $h(q)$ and $\alpha(q)$ would be independent of q . On the other hand, for the time series which exhibit multifractality, the discussed quantifiers will typically be monotonically decreasing functions. Nonetheless, for certain behaviors of the series, for instance if only large (small) local fluctuations prevail the $h(q)$ dependence will show plateau for positive (negative) values of q . This feature cause the truncation of the left (right) branch of the corresponding mf-spectrum shown in the figure 2.

Table 1: The parameters of the mf-spectrum, calculated for three states of muscle activity respectively for the raw and integrated data.

Object	maximal contraction	task	relaxation
Hurst exponent $H^{int} = h^{int}(2)$			
Professional	0.714	0.31	0.664
Amateur	1.01	0.67	0.772
Hurst exponent $H = h(2)$			
Professional	0.062	-0.147	0.031
Amateur	0.094	-0.017	0.025
$h_{max}^{int} = h^{int}(0)$			
Professional	0.759	1.06	0.755
Amateur	0.981	1.14	1.05
$h_{max} = h(0)$			
Professional	0.111	0.166	0.027
Amateur	0.149	0.239	0.175
$\Delta_{1/2}^{int}$			
Professional	0.045	0.756	0.092
Amateur	0.031	0.467	0.282
$\Delta_{1/2}$			
Professional	0.0485	0.312	0.0044
Amateur	0.0556	0.256	0.150

There are several parameters we can use to effectively describe mf-spectrum and, consequently, the signal which lies behind it. In the table 1 we have collected the typical quantifiers – the values of the typical Hurst exponent $H = h(2)$, singularity exponent located at the maximum of the spectrum h_{max} , and spectrum half-width $\Delta_{1/2}$ defined as the absolute value of the difference between Hurst exponent and h_{max} , all calculated for both row and integrated data. The integrated data are calculated as cumulative sums of the original (raw) signal. In the case of the monofractal signal the spectrum of the integrated signal is usually the same as for the raw one, but shifted by 1 to the right. Lower values of this difference suggest that the obtained mf-spectra have other than monofractal scaling. Again, for almost all factors there is a significant difference between amateur and professional for two states – at the relaxation and during the assumed task. For maximum contraction the only factor which distinguishes the professional and amateur is the Hurst exponent calculated for integrated data.

5 Summary and conclusions

The comparison of the kinesiological electromyographic signal between a professional (highly trained) and an amateur was presented for the three typical states of work of the human musculo-skeletal system. Based on the multifractal detrended analysis we have shown the differences and similarities for the data fluctuations. The main message which can be drawn from the analysis is that the locomotor apparatus for the trained person would require much less energy to perform tasks as it's work would produce much smaller local fluctuations. The multifractal spectrum would in turn look more similar to the one at the rest state. On the other hand there is much less chance to distinguish the depth of training between two persons if one would look at the sEMG data assembled at the strong muscle tension. The muscle cell membranes will in this case tend to react with much higher voltage of the electrical potential as these cells will be much stronger activated neurologically.

In conclusions we would like to suggest the possible application for automatic verification of abilities for performing complex tasks based on the fluctuation analysis. If the person's multifractal spectrum would be wide with no truncation on the right side (at higher singularity exponents $\alpha(q)$) than the low and high local fluctuation would

be equally probable. This means that the examined person still operates with too much stress and struggles with the task, therefore some more training would still be needed.

Acknowledgements

Authors would like to thank Danuta Makowiec and Jan Żebrowski for valuable discussions. This work was partially supported by the Polish Ministry of Science and Higher Education (Grant K/ZDS/003962).

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